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Artificial Neural Network for Classifying Injected Materials under Ultrasonography

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Abstract. We have constructed an artificial neural network (ANN) architecture to classify four different classes of ultrasonography recorded from a jelly box phantom that was injected by iron, glass, or plastic marble, or without any injection. This jelly box was made as a phantom of a human body, and the injected materials were the cancers. The small size of the injected materials caused only little disturbances those could not easily distinguished by human eyes. Therefore, ANN was used for classifying the different kind of the injected materials. The number of original imagestaken from ultrasonographs were not so many, therefore we did data augmentation for providing large enough dataset that fed into ANN. The data augmentation was constructed by pixel shifting in horizontal and vertical directions. The procedure proposed here produced 98.2% accuracy for predicting test dataset, though the result was sensitive to the choice of augmentation area.

Keywords: Artificial Neural Network, Tensorflow, Multiclass Classification

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1. Introduction

In this article, we describe the use of machine learning, especially the artificial neural network (ANN), in classifying different injected objects in a phantom by analyzing their ultrasonography images. The phantom was made from jelly, a kind of translucent food. The injected materials were iron, glass and plastic marbles. Due to the small size of the objects, the resulting images were not easily classified by human eyes, therefore any computational method could help to solve the problem. Here, we used ANN to make prediction for classifying an unknown injected material. The method has given good results, i.e. it can give more than 95% accuracy for the test datasets. It should be very useful for predicting the density class of any injected material outside the database used in this research by giving appropriate assumption.

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1.1. Neural Network Research Based Review

Neural network has been used widely in different areas and it is now still growing fast as a powerful learning machine to use in artificial intelligence as reported by Lecun [1]. For some medical or related areas, here we give some examples. Moein et.al [2] reported several application of neural network in medical diagnosis, for examples are cancer, hepatitis, heart diagnosis, pattern recognition and also in drug development. Lee et.al. [3] uses ANN to predict prostate cancer using transrectal ultrasonography, using 684 patients database. Lee has compared two difference ANN methods depending on the available additional data. For more complicated medical imaging, Convolutional Neural Network (CNN) is used instead of ANN. For example, Wu et.al. [4] used CNN for analyzing brain tumors with MRI dataset. Zhang [5] also used ANN and CNN to classify breast cancers through mammograms. Dealing with unstructured radiology reports, Pandey [6] used a specific CNN method, i.e. Natural language processing (NLP) approach to extract clinical terms. Zhou [7] used CNN for identifying capsule defects. Almezhghwi [8] used a branch of CNN, i.e. GAN, to classify four difference blood cells.

Our analysis was based on the ANN given by Tensorflow module. The basic procedures are given in many papers, for example in [9]. When we did this research, we had only small size database. In order to have high accuracy, we made some experiments in creating simple data augmentation before running ANN. Actually, data augmentation procedure is also provided by Tensorflow, and often used by researchers, for example is the work of Dong et.al. [10].

1.2. Mathematical Background of ANN

ANN is a method for calculating the optimal parameters used for fitting data target into a (quasi) linear model. The simplest one of classification procedures is to connect between a single input vector, $\boldsymbol{x}$, to a output vector, $\boldsymbol{y}$, through a composition of an activation function and a linear equation:

$$\mathbf{y} = \sigma(\mathbf{x} \cdot \mathbf{w} + \mathbf{b}) \tag{1}$$

where σ is the activation function, **w** and **b** are weights and bias matrix respectively. When we add one hidden layer between input and output, we add also one more composition function as

$$\mathbf{y} = \sigma_2(\sigma_1(\mathbf{x} \cdot \mathbf{w}_1 + \mathbf{b}_1) \cdot \mathbf{w}_2 + \mathbf{b}_2) \tag{2}$$

Therefore, a long ANN (usually known as deep learning) will have long form of composition function too, because it has many hidden layers.

The activation function can be chosen differently for different layers [11]. In this research, we use only two different types, i.e.

$$\sigma_h(z) = \max(0, z) \tag{3}$$

and

$$\sigma_f(z)_i = \exp(z_i) / \sum_{k=1}^{K} \exp(z_k)) \tag{4}$$

Here, σ_h is called by ReLU (rectified linear unit) or threshold function [12] and used for all hidden layers and σ_f is called by Softmax [13] and used only for the final (or output) layer that produces K classes.

The goal of ANN is to calculate the best weights **w** and bias **b** (in all layers) that minimize the cross-entropy loss function defined as [14]

$$L(\mathbf{w}, \mathbf{b}) = \sum_{i=1}^{K} -y_i \log \hat{y}_i(\mathbf{w}, \mathbf{b}) \tag{5}$$

Here, $\hat{y}$ is the function that has to be calculated such that it becomes very close to the data target y. The minimization uses Adaptive Moment Estimation (Adam) method [15].

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2. Methods

There were two steps of works. First, the preparation of sample and data acquisition using 2 dimensional USG Mindray DP-10; second, the data augmentation and ANN architecture.

2.1. Preparation and Data Acquisition

First, we made a phantom that simulate a human body using jelly. Jelly is a material for making food, it has clear or translucent color. A soft-solid box of jelly, with size 15cm × 15 cm × 10 cm, was easily created by cooking 40-gram jelly powder in 2.25 liter water. In room temperature, it became a soft-solid form. We cut the jelly box at the center in such a way that a marble can be placed into the center or taken away from it. USG Mindray DP-10 was used to scan the jelly box with a marble inside it. There were three different marbles, and each marble was scanned 16 times with variations of the position of USG convex transducer 35C50EB. The data acquisition was situated as shown in Figure 1. Without marble, the jelly box was also scanned 16 times. The physical properties of the injected marbles is given in Table 1.

Table 1. The properties of the injected marbles in the jelly box

Material	Diameter (mm)	Mass (g)	Density (g/cm^3)
Iron marble	17.34	21	7.7
Glass marble	16.30	6	2.6
Plastic marble	15.75	2	0.98
Jelly box			1.14

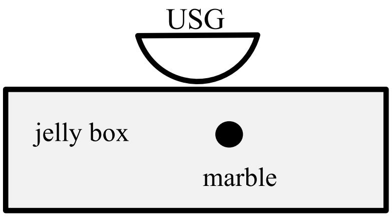

Figure 1. A marble inside the jelly box is scanned using USG convex transducer 35C50EB

2.2. Data Augmentation and ANN Architecture

Each image taken from USG was augmented using a fix size of box, i.e. 280×200×3 pixels, that shifted horizontally and vertically as shown in Figure 2. Using 5 times horizontal shifting and 5 times vertical shifting, we got 5×5=25 data for each image, therefore we had 25×16×4=1600 images as the dataset.

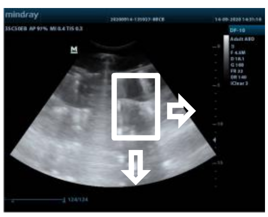

Figure 2. Data augmentation using

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The architect of ANN proposed here is shown in Figure 3. Each data image taken from the augmentation has to be reshaped from 3 dimensional (RGB) image of size [280, 200, 3] into 1 dimensional image with size [1, 280×200×3] before flowing it into the input layer of ANN that consists of 64 neurons. After reshaping data, all data flow to the first hidden layer with 32 neurons, to the second one with 16 neurons and finally to the final (output) layer that has to classify the image into 4 categorical classes. ANN will calculate the best weights and bias and also return the accuracy.

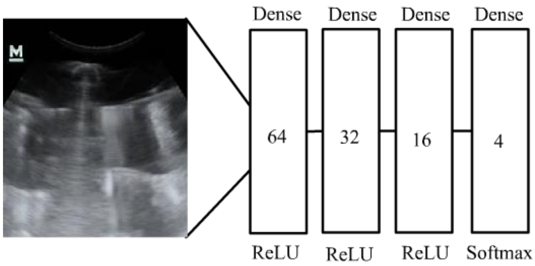

Figure 3. The architect of ANN used in this research.

The dataset that consists of 1600 data images has to be split into two parts, i.e. training dataset and testing dataset in order to make appropriate analysis. Here we used 21.9% data for testing (or 350 images from 1600).

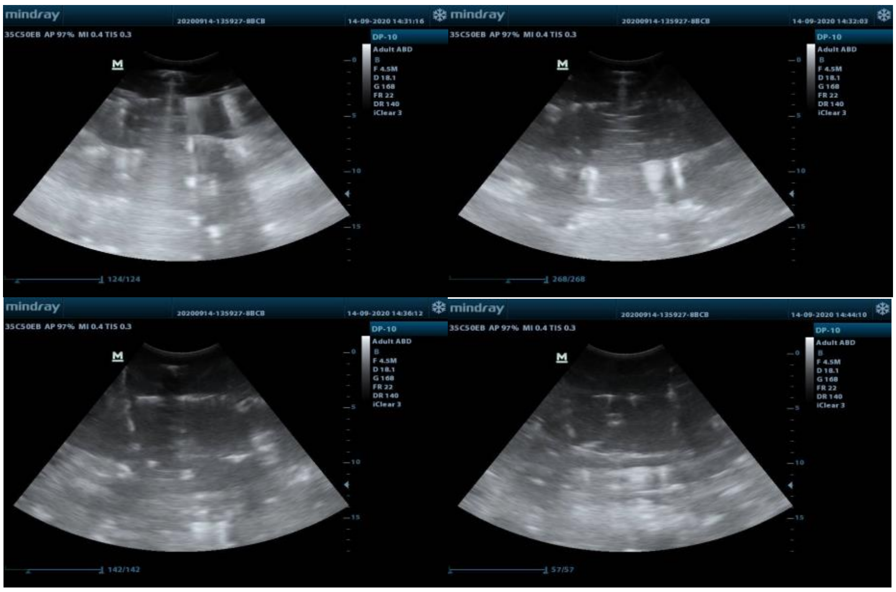

Figure 4. Four different classes: iron marble (left-top), glass marble (right-top), plastic marble (left-bottom), without marble (right-bottom).

3. Results and Discussion

3.1. Data Acquisition Results

From Figure 4, we understood that a manual attempt to classify any injected object into jelly box using human eyes was not easy, though we could differ the empty (without marble) box with the filled box. It

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simulates a situation for a radiologist to predict whether there is a strange object inside a known (or normal) human body or not. The small size of the injected material in the jelly box caused only little perturbation in the image, therefore we could select only a specific range in the image and did some experiments around the selected position by doing data augmentation. The accuracy depends on the choice of the selected area. Here we reported only the best we could achieve. The accuracy is defined as

$$a = \frac{N-f}{N} \tag{6}$$

In Equation (6), N is the number data and f is the number of incorrect predictions.

3.2. The ANN Result and Discussion

According to Figure 5, the algorithm converges after 35 epochs, though the profile of the loss function and the accuracy are not smooth enough. The accuracy of the testing datasets reaches 98.2%. Unfortunately, this result is sensitive to the choice of area for data augmentation. The accuracy may vary very wide if we wrongly select the area. Therefore, other robust methods in the preprocessing data, such as data augmentation, have to be investigated more if we want to use ANN, before migrating to convolution neural network.

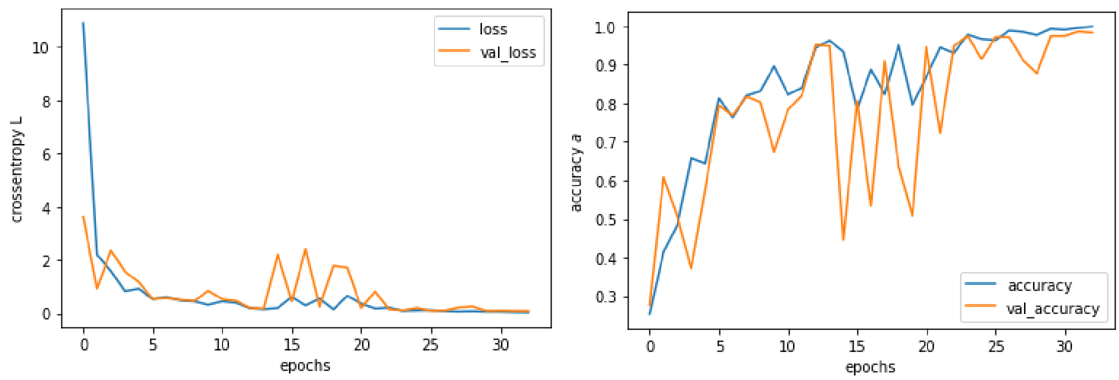

Figure 5. The profile of the loss function (left) for training dataset (loss) and testing dataset (val_loss), and the accuracy for training dataset (accuracy) and testing dataset (val_accuracy)

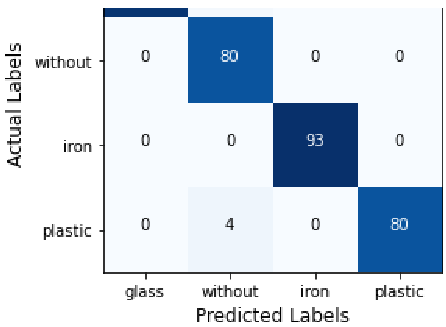

Figure 6. The confusion matrix of the prediction of the testing dataset. It shows 98.2% accuracy.

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The confusion matrix in Figure 6 shows that the incorrect predictions mainly come from the plastic marbles those are wrongly predicted as the class without marble. But it shows only a small fraction, i.e. 4/80, and it shows a promising method to distinguish a material that has density near the phantom (jelly box) density as given in Table 1.

4. Conclusion

We have reported that ANN can be used for classifying injected materials, such as iron marble, glass marble and plastic marble, that injected in a jelly box. Data augmentation from the ultrasonography images and ANN architecture proposed in this paper produced 98.2% accuracy of prediction, though the result was sensitive to the choice of augmentation area.

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